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Measurements of Hydrological Variables from Satellite: Application to Mediterranean Regions

Francesca Sini, Giorgio Boni and Dara Entekhabi

Abstract The present research is devoted to investigate the surface energy balance and estimate the surface energy fluxes and the evaporative fraction over extended areas.

The fluxes of heat and moisture at the land surface determine the regional water balance, and they affect the development and evolution of weather and climate systems as well as hydrological events. Research and model simulations are showing how forecast of extreme events significantly improves using distributed information of soil moisture or heat surface fluxes. Furthermore recent applications prove how the use of soil moisture indexes can facilitate the calibration of distributed hydrological models on ungauged basins. Following these rising needs of land surface measurements, for different application field, satellite data assimilation could be used to supply the estimation of those variables.

Data assimilation techniques provide a useful framework which allow to combine measurements and model to produce an optimal and dynamically consistent estimate of the evolving state of the system. A variational assimilation scheme is here used as basis to estimate variables related to atmosphere-surface interaction processes. Land Surface Temperature, estimated both from polar and geostationary satellite platform, is the assimilated variable. Introducing precipitation information allows a more robust estimation scheme and a better simulation of soil moisture condition and surface fluxes partitioning. The model is implemented over mediterranean regions assimilating SEVIRI, AVHRR and MODIS data.

Keywords Surface energy balance · Data assimilation · Remote sensing · Land surface temperature · Evaporative fraction

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1 Introduction

Latest studies have shown that monitoring heat, mass and energy fluxes over extended areas is becoming more and more important for investigating the dynamics balance of water resource. The estimation of surface water availability and surface energy balance terms based on remotely sensed data is advantageous because limited in situ measurements are available and spatial heterogeneity precludes large-scale characterization of their fields.

The introduction of this kind of data requires a reformulation of both conceptual frameworks and operational models in hydrology (Entekhabi et al., 1999).

Remote sensing measurements provide the necessary spatial coverage for the characterization of energy and mass fluxes at the soil surface; on the other hand they are not direct observations of land surface hydrological states and parameters. Remote sensing instruments generally measure radiobrightness or backscatter that relate to the state of the surface [e.g. Land Surface Temperature (LST)] or to its properties (e.g. albedo, vegetation indexes...). Fluxes from the surface do not have a unique signature that can be detected by satellite technologies. Remotely sensed measurements need to be merged into models or empirical relationship must be found in order to retrieve variables related to land-atmosphere processes.

In the works of Gilles et al. (1997) and Moran et al. (1994) empirical relations to infer the surface evaporation rate are based on position in the space defined by LST and an optical Vegetation Index. Measurements of these two surface properties are then used to produce maps of land surface evaporation. Scatterplots of vegetation index and land surface temperature show that regions with similar soil moisture or evaporation tend to group together.

A more physical approach is to use LST satellite products, combined with surface air micrometeorology measurements, to estimate the contribution of each flux component to the total surface energy balance.

Surface radiometric temperature observations are utilized to solve the surface energy balance and partition incoming radiation into various flux components. These methodologies are typical diagnostic in nature and therefore make flux predictions only for instant in which LST observation is available (Norman et al., 1995; Bastiaansen et al., 1998; Jiang and Islam, 2001; Su, 2002). Ancillary land surface parameters such as leaf area index (LAI), surface roughness and the fractional coverage of vegetation are required to accurately estimate near-surface resistance to the transfer of momentum, energy and water.

An alternative approach to extract such information is to use data assimilation techniques that can take advantage from merging the remotely sensed data by different sensors and with different spatial scales. Furthermore these methods can impose efficiently dynamic constraint using a model of the system as part of the statistical state estimation. This approach, in particular the variational technique, has been deeply investigated and an innovative satellite assimilation scheme is presented.

In the following sections an overview on data assimilation techniques, LST and cloud mask most popular algorithms is reported. Finally research outline and

examples of assimilation scheme implementation, applied to Italian regions, are introduced.

2 Data Assimilation Techniques

The increasing number of satellite platforms is providing a better distributed and spatial coverage of land surface and atmospheric measurements. Remote sensing measurements offer a promising new source of information about the land surface. However, this information is usually only indirectly related to variables of hydrologic interest (through nonlinear radiative transfer equations).

The problem of estimating hydrologic variables from remote sensing observations often requires the solution of ill-posed inverse problems. Constraints derived from physically-based hydrologic models need to be imposed in order to obtain unique solutions.

Data assimilation provides a theoretical framework and practical methods for addressing such constrained estimation problems. It allows us to merge measurements and physical models under the supposition that both provide useful information about the state of the system, while containing measurement and model errors respectively. By appropriately weighting the sources of error in both, the goal is to ultimately produce a statistically optimal and dynamically consistent estimate of the evolving state of the system.

Differences approaches on assimilating data can be used. Sequential assimilation considers observation made in the past until the time of analysis, which is the case of real-time assimilation system. In non sequential or retrospective assimilation the observation from the future can be used in a reanalysis exercise. Another distinction can be made between methods that are intermittent, where observations can be processed in small batches, or continuous in time, where longer periods are considered and the correction the analysed state is smooth in time (Bouttier and Courtier, 1999). Compromises between these approaches are possible.

In meteorology and oceanography there is a well established history of using data assimilation and many assimilation techniques have been developed, differing in numerical cost, optimality and suistability for real-time applications.

In Ghil and Manalotte-Rizzoli (1991) a good comparison of the various techniques is provided. In the recent year data assimilation has been also applied to land-atmosphere interaction research field. Hydrologic data assimilation as a state estimation problem has only very recently become a topic of widespread interest. Theoretical bases on data assimilation techniques applicable to hydrologic and geologic science are reported in Castelli and Entekhabi (2002).

Data assimilation techniques can be roughly divided in two main categories:

1. Variational techniques (3DVAR, 4DVAR)
2. Derived Kalman Filter techniques (filter and smoother methods)

These approaches will be briefly described in the following subsections.

2.1 Variational Techniques

Variational data assimilation techniques have a well-established history in meteorology and oceanography (Li et al., 1993; Bennett et al., 1998 . . .). In the last ten years these techniques have begun also to be applied in land surface applications (Castelli et al., 1999; Boni et al., 2001b; Reichle et al., 2001; Margulis and Entekhabi, 2002; Caparrini, 2001, 2003).

The three-dimensional (the space dimensions) variational data assimilation (3DVAR) uses one-time observations to produce initial conditions statistically through forecast fields and observational data. The four-dimensional (with time as the fourth dimension) variational data assimilation (4DVAR) differs from the 3DVAR for including the dynamics evolution of the model in the assimilation (Holm, 2003).

The central concept in variational data is the adjoint model. This is obtained by linearizing the forward (forecast) model along a trajectory producing the tangent-linear model, and obtaining the adjoint. In other word, it is based on an inverse physical constraint derived from the forward model and the assimilation problem is then redefined as an iterative process with which we want to minimize the gap between observed fields and initial model states. Thus variational techniques require differentiable models. Process noise can only be additive and Gaussian. Any changes in model structure require the reformulation of the adjoint, so the model framework can't be modified easily. All data are used in a single batch window to estimate the state and obtain the best solution. Formally it is an optimization problem with equality constraints which may be solved through the Lagrange multipliers technique.

Recent advances in land data assimilation have yielded variational techniques designed to solve the surface energy balance on multisensor imagery sequences of surface radiometric temperature (Caparrini et al., 2004a).

This approach has a number of potential advantages over existing diagnostic models, including the ability to make energy flux predictions between observation times and reduced requirements for ancillary parameter estimation (Crow and Kustas, 2005).

The variational scheme is a powerful choice since it uses all the observations from both polar and geostationary platforms, with different resolution, in an assimilation window (daily interval) and improves the estimation of the unknowns by repeatedly integrating forwards and backwards through the model. The LST is the assimilated variable into a force-restore equation for surface temperature. It is an optimal state variable as it contains implicit information about the partitioning of available energy into latent, sensible and ground heat fluxes in the way in which it evolves during the day. It is shown that sequential surface temperature data contain useful information on dynamics energy balance and may be used to improve the energy fluxes estimation. Net Radiation, wind speed and air temperature are the forcing meteorological data. The variational approaches demonstrate promise for flux retrievals at dry and lightly vegetated sites, however a less accurate prediction appear over wet and/or vegetated land surfaces. Over densely vegetated and wet surfaces the presented variational smoothed approaches could be ill-posed, as there are small or non-variable differences between surface and air temperature.

2.2 Derived Kalman Filter Techniques

An important difference between the Kalman Filter and variational technique is that the first performs an analysis at each time step of the model, using only the observations available during that timestep, the second all observations in the assimilation window (Holm, 2003). If we compare the Kalman Filter integration and the 4DVAR integration inside the assimilation window of 4DVAR, the variational solution is a continuous curve, whereas the Kalman Filter has jumps at each timestep. The word Filter characterizes an assimilation techniques that uses only observation from the past to perform each analysis. An algorithm that uses observations from both past and future is called a smoother. 4DVAR can be regarded as a smoother.

In the Kalman Filter the errors are considered to evolve linearly during a single timestep of the model. It provides the optimal state estimate for linear system, therefore of little use in hydrological applications where the physical model equations are often nonlinear and contain thresholds. Extended Kalman Filter (EKF) for nonlinear systems approximate expressions has been developed and been successfully applied to the land data assimilation problem (Entekhabi et al., 1994; Walker and Houser, 2001), but its use in this application would require derivation of a tangent linear model to approximate the land surface model, as well as techniques to threat the instabilities which might arise from such an approximation (Dunne and Entekhabi, 2004a).

The EKF is a first-order linearization approximation of the nonlinear system. An alternative sequential estimation technique for non linear problems is the Ensemble Kalman Filter (EnKF).

An ensemble of model states is integrated forward in time using the nonlinear forward model with replicates of system noise. At update times, the error covariance is calculated from the ensemble. The tradition update equation from the classical Kalman Filter is used, with the Kalman gain calculated from the error covariances provided by the ensemble. This technique has been successfully implemented (Reichle et al., 2002; Margulis et al., 2001; Crow and Wood, 2003).

The Ensemble Kalman Smoothers (EnKS) (Evensen and Leeuwen, 2000) are an extension of the EnKF in which information from the observation at update time t is used to update, not just the state estimate at that update time, but also at previous time, t' . The EnKF solution is the “first guess” of the EnKS (Dunne and Entekhabi, 2006).

Ensemble-based methods are appealing as they obviate the need for an adjoint. Any model can be used. But estimates are conditioned on past measurements only.

3 Land Surface Temperature Estimation

In order to integrate effectively the use of remotely sensed images into a variational scheme based on surface energy balance model, the development of accurate and reliable methodologies of LST estimation from remote data turns out to be mandatory.

The direct in situ measurement is made very difficult by the extremely large temperature gradients that commonly occur near the surface in the air and the soil media, by the finite dimensions of the temperature sensors and by the difficulties of ventilating and shielding the sensor when it is placed at the surface. Remote sensing techniques appear to be the new frontiers for detecting this variable.

Over the decades, the techniques for measuring the Sea Surface Temperature (SST) and LST from space radiometry have improved in terms of method, instrumentation, as well as computation. The success in SST estimation made researchers anticipate similar success for LST. In contrast, it was identified that the retrieval of this variable is much more complicated. Apart from the attenuation in the transmitted radiance caused by the atmosphere, the problem is also complicated by the highly variable land surface emissivity, as its dynamics has a wider range and can vary over short distances. Moreover, a proper LST validation is also difficult because the derived LST is representative for the whole pixel, while point temperatures measurements can vary over short distances.

In order to obtain LST from space radiometry, three main effects have to be considered and corrected for: atmospheric, angular and emissivity effect. Besides the complications due to atmospheric attenuation, a direct separation of LST and emissivity from passive radiometer measurements alone is not feasible because the problem is underdetermined: for a sensor with N spectral channel, there are N measurements but $N+1$ unknowns. For resolving this ill-posed problem, additional assumptions are necessary to constrain the extra degree of freedom, which has led to different temperature-emissivity separation methods. As land surface emissivity is less variable, in space and time than LST, it is reasonable to estimate emissivity first and then calculate LST (Dash, 2004). Satellite sensors observe the land surface at different viewing geometries and, therefore estimated brightness temperatures must also be compensated for the zenith angle. LST algorithms must account for this effect in order to provide results that are independent of observation geometry.

A recent comprehensive review of both LST and emissivity estimation techniques from passive sensor data is given by Dash et al. (2002b). The prevalent methods of LST estimation that required a priori surface emissivity information could be grouped as follows:

- *Single channel method*: This method uses radiance in one infrared window channel and correct the atmospheric effects to determine LSTs (Price, 1983; Susskind et al., 1983). It requires that the vertical and horizontal distribution of temperature and water vapor in the atmosphere is accurately known. Possible sources for atmospheric profiles are vertical sounding instruments on satellites, data from numerical weather prediction models and radiosondes. It uses a radiative transfer model to simulate satellite measurements over a range of surface parameters for a given atmosphere.
- *Multi angle method*: Assuming that the atmospheric column is spatially uniform, the method exploits the differential absorption due to different atmospheric slant path-lengths when the same object is observed under different viewing angles for a given channel (Sobrino et al., 1996).

- *Split window technique*: Due to its operational simplicity, it is the most popular method. It uses differential absorption between two channels within one atmospheric window in order to eliminate the atmospheric influence, and calculates LST as a linear combination of two brightness temperatures.

It is due to underline however that its coefficients are strictly valid only for the data-set used to derived them and for the sensor and do not always reflect the real situation. The algorithms and instrumental approach have evolved from the use of a single window channel on a polar satellite to the use of multispectral radiometer observations from both polar orbiting and geostationary satellites. An overview of the most popular algorithms is reported in the following.

Most studies on LST have focused on the use of polar-orbiting satellite systems, such as NOAA-AVHRR and MODIS. These studies indicate that it is possible to retrieve LST at a reasonable accuracy (with a Root Mean Square Error of 1–3 K) from current operational and research satellite-borne visible/infrared radiometers.

Price (1984) algorithm was one of the first methods focusing on retrieval LST from AVHRR. By simplifying the atmospheric influence and using radiative transfer theory, Price developed a split window which has been used extensively.

Ulivieri et al. (1992) formulated a more reliable approach, that has been applied to different locations with good results.

Based on radiative transfer theory and numerical simulations, Becker and Li (1990a) proposed a linear combination of the temperature of channel 4 and 5, in which the local coefficients depend on surface emissivity by they are independent of the atmospheric effect. The coefficients were calculated from numerical simulations and accounted for the local atmospheric effect.

Sobrino et al. (1991) related the coefficients to the state of the atmosphere as well as to surface emissivity. Total amount of water vapour in atmosphere and atmospheric absorption coefficient are taking into account.

Kerr et al. (1983) proposed a semi-empirical algorithm that classifies surfaces either as bare soil or as vegetated area. The two classes are obtained calculating the area fraction from Normalized Difference Vegetation Index (NDVI). Values of minimum and maximum of NDVI in the area of study are required. The LST is defined as a linear combination of bare soil temperature and temperature of vegetated area.

In the formulation of Coll et al. (1994) it was considered also the effect of satellite zenith angle. Coefficients are related to atmospheric transmissivity for nadir viewing and the type of atmosphere.

Becker and Li (1995) modified their previous algorithms by including the atmospheric water vapour content. Coefficients were calculated using the low resolution transmittance (LOWTRAN) code. Wan and Dozier (1996) proposed a Generalized Split window Method (GSM) for retrieving LST either form AVHRR and MODIS data. Accurate radiative transfer simulations showed that the coefficients of the split window algorithm for LST must vary with the viewing angle. This algorithm is less sensitive to uncertainty in emissivity and to instrument quantization error. NASA Land Surface Temperature Group provides per-pixel LST products with an accuracy better than 1K from MODIS data. They use two LST algorithms,

one is the GSM and another is the physics based day/night LST method (Wan and Li, 1997).

The temporal measurements frequency of the polar orbiting satellite measurements is approximately 2 times per day, which is inadequate for many applications (Sun et al., 2004). Experiments on the effects of sparse temporal sampling showed that observation within a 3 h window around the mean time of daily maximum is most effective to capture information on the cumulative heating and available energy partitioning at the land surface (Boni et al., 2001a). For the purpose of land surface energy balance estimation, based on thermal remote sensing, sampling strategies and satellite orbits that yields data at least near the peak of the diurnal cycle may then be considered. Geostationary satellites, as they provide diurnal coverage, are particularly suitable for investigating land-surface interaction processes. Otherwise less work has been done on retrieving LST from radiometers on board of those satellites.

Prata and Cecket (1999) investigated LST retrieval from the Japanese Geostationary Meteorological Satellite (GMS)-5, using a split window algorithm. LST from GOES-8 was addressed by Sun and Pinker (2003). Two algorithms are developed based on radiative transfer theory; one is similar to the classical split window approach used to derive SST, while the other is a three channel algorithms. The three-channel LST algorithm aims to improve atmospheric correction by utilizing the characteristics of the middle-infrared (MIR) band. Effects of both the atmospheric and the surface emissivity are accounted for. Gottsche Olesen (2001) modeled the diurnal cycle of brightness temperature extracted from METEOSAT data.

Dash et al. (2002a) investigated the potential of MSG-SEVIRI radiometer for surface temperature and emissivity estimation. On the basis of SEVIRI's spectral and temporal resolutions the Thermal Infrared Spectral Indices (TISI) day/night method is selected for estimating emissivity. In order to obtain a fast and accurate procedure for the estimation of channel emissivities and LST, the combination of the TISI day/night method with a neural network (NN) for calculating atmospheric variables is proposed.

Sobrino and Romaguera (2004) developed a physical-based split window algorithm for retrieving the surface temperature from SEVIRI data in the thermal infrared bands 10.8 e 12.0 μ m. The proposed algorithm takes into account the angular dependence and it was tested with simulated SEVIRI data over a wide range of atmospheric and surface conditions.

Peres and DaCamara (2004) suggests that an algorithm based on the two-temperature method (TTM) may be used as a complementary method to split window algorithms over areas where LSE is not well known a priori.

The pre-operative LAND-SAF LST products for SEVIRI data is derived by the GSW algorithm, adapted to SEVIRI data (Madeira, 2002). Look-up table of optimal coefficients is previously determined at individual classes of satellite viewing angles, and covering different ranges of water vapour and near-surface air temperature. The retrieval of land surface emissivity is based on the Vegetation Cover Method (VCM; Caselles et al., 1997) that relies on the use of a geometrical model to compute an effective emissivity based on the knowledge of the Fractional Vegetation Cover (FVC), also retrieved by the LSA SAF.

Recent studies are also focusing on applying Support Vector Machines techniques (Cristianini and Shawe-Taylor, 2000), recently introduced in kernel based architectures, to estimate LST.

Only few methods exist which do not strickly require a priori emissivity information and perform simultaneous retrievals of the geophysical parameters (Wan and Li, 1997; Dash et al., 2002a).

4 Cloud Mask Algorithms

When using satellite imagery to study the land surface it is important to eliminate all pixels that could possibly contain any source of cloud contamination, even at the expense of removing some clear pixels as well. Maps of vegetation index and land/sea surface temperature must be cleaned from cloudy contamination, as values calculated over those pixels are not related with land surface characteristics.

Most of the work on cloud estimation has been done using window channels on imaging instruments. Some of them are simple and fast, some are more computationally intensive and others require empirical data, simulated datasets, radiative transfer models or some sort of training in order to accurately identify clouds. The most popular techniques are briefly described as follow.

- *Threshold technique*: Over the year, a number of cloud mask methods applied to AVHRR and MODIS data, has been developed using pixel-by pixel processing (Saunders and Kriebel, 1988; Derrien et al., 1993; Hutchison et al., 1997; Caparrini, 2001; Vemury et al., 2001; Ackerman et al., 2002; Chen et al., 2002; Di Vittorio and Emery, 2002). The simplicity of this technique makes it attractive and easy to implement for operative purposes. These methods use approaches based on fixed or dynamic thresholds obtained from single or combination of channels in the visible and thermal bands of the spectrum. This involves finding high reflectance pixels in visible channels and low brightness temperature in infrared channels. A thresholds is set such that if a pixel is brighter or colder than the threshold, the pixel is assumed to be cloud covered. The fractional area covered with cloud is simply the ratio of the number of cloudy pixels to the total number of pixels. Thresholds cloud detection techniques are most effective at night over water. Over land, the threshold approach is further complicated by the fact that the emissivity in the infrared window varies appreciably with soil and vegetation type. It is also difficult to classify partly cloudy pixels.
- *Multispectral technique*: Multispectral approaches offer several opportunities for improved cloud detection. In this category it is grouped the cloud retrieval techniques that rely on radiance measurements at two or more wavelengths and use simple models to make retrievals.

The algorithm developed by the Satellite Application Facility (SAF) on support to Nowcasting and Very Short-Range Forecasting of the EUMETSAT Ground Segment (see <http://nwcsaf.inm.es>), is based on multispectral threshold technique

applied to each pixel of the image. A first series of tests allows the identification of pixels contaminated by clouds or snow/ice. The tests, applied to land or sea pixels, depend on the solar illumination and on the viewing angles. Most thresholds are determined from satellite-dependent look-up tables using as input the viewing geometry, NWP forecast fields and ancillary data. Some thresholds are empirical constant or satellite-dependent values. A spatial filtering is applied, allowing to reclassify pixels having a class type different from their neighbours. A test is applied to cloud contaminated pixels to check whether the cloud cover is opaque and completely fills the Field Of View. This first series of tests allows to determine the cloud cover category of each pixel (cloud-free, cloud contaminated, cloud filled, snow/ice contaminated or undefined/non processed). A second process, allowing the identification of dust clouds and volcanic ash clouds, is applied to all pixels.

- *Radiative transfer technique*: Radiative transfer techniques are similar to the multispectral, but they use the results of more complex radiative transfer calculations to make retrievals. The advantage of using radiative transfer calculations is that they allow the retrieval of parameters, such as cloud optical depth and microphysical properties, that are not retrievable with other methods.
- *Histogram technique*: Histogram techniques serve as alternates to threshold techniques (Kidder and Haar, 1995, Chapter 6). The basic idea is that a histogram of the pixels in an area will show clusters of pixels that represents cloud or surface types. The histograms have as many dimensions as the number of channels of data. Unfortunately some histograms are much more difficult to interpret because some cloud or surface types are too variable to form a local maximum in the histogram.

Less common are techniques that use neural network-type algorithms trained on manually cloud-masked data (Uddstrom et al., 2001). Mixed techniques are used to detect and classify clouds too.

5 Satellite Data Assimilation: Application to Mediterranean Regions

The variational literature described in Section 2.1 represents the starting point of the research activity, that aims to the formulation of a robust model for the estimation of the moisture conditions and the energy fluxes at the soil surface. The main goal is to improve the estimation of evaporative fraction and latent and sensible fluxes over wet soil and vegetate areas. The model should be implemented for widespread application and the outputs should be used for both hydrological and meteorological applications. The multiscale scheme introduced by Caparrini et al. (2004a), the “combined source” version, is modified in order to take into account the contribution of precipitation observed data. In the original variational assimilation scheme, no rainfall data was used. The wide availability of rainfall observations from different

sensors (raingauges, radars, satellites) makes these data easily available and useful for several applications. In the following a summary description of model and its applications is provided. Mayor details could be find in Sini (2005). The variational assimilation scheme is based on the definition of a penalty function that incorporates, as physical constraint through Lagrange multipliers, a simple surface energy balance model for the prediction of LST evolution.

The first term of the penalty function is a quadratic measure of the misfit between model predictions and LST observation. This has to be minimized on the parameter space under constraint. The dynamic equation of heat diffusion in the soil, in its simplified force restore approximation, is the model physical constraint:

$$\frac{dT_s}{dt} = 2\sqrt{\pi\omega} \frac{R_n - H - LE}{P} - 2\pi\omega(T_s - T_{deep}) \quad (1)$$

where T_s is the LST, ω is the dominant frequency, P is the effective thermal inertia, R_n is the net radiation at the surface, H and LE are the turbulent sensible and latent heat fluxes, using the bulk transfer formulation, and T_{deep} is a “restoring” deep ground temperature.

A simplified mass balance equation, the Antecedent Precipitation Index (API) is used to link the precipitation field into the model scheme:

$$\frac{d(API)}{dt} = -\gamma(API) + I \quad (2)$$

where γ is the decay API parameter and I the intensity of precipitation. It represents a soil saturation index obtained by means of a composition of previous precipitations (WMO, 1983). For its simplicity and differentiable form it is a suitable equation to be used inside a variational scheme. The saturation effect could be taken into account estimating the daily decay factor inside the assimilation process.

The constraint equation can be written in terms of Evaporative Fraction (EF), defined as the ratio between the latent flux and the sum of turbulent fluxes, a useful parameter as it is almost constant during the daytime (Crago, 1996; Crago and Brutsaert, 1996).

An empirical relation between API and EF is found in order to join precipitation input into the force restore equation:

$$EF = a + b \frac{\arctan(K \overline{API})}{\pi} \quad (3)$$

where \overline{API} is the mean daily API, K a land use related parameter, a and b constant terms. In this way both the dynamics equation of heat diffusion and API are used as constraints with the adjoint technique.

The neutral bulk transfer coefficient $(C_B)_N$, supposed equal for sensible and latent heat fluxes, K and γ , imposed positive over all domain, are the estimated parameters. The first two are forced to have a monthly variability and the last one changes on a

daily scale. Ancillary data on soil and vegetation features are not necessary as the parameters are evaluated inside the assimilation scheme. Land surface temperature, from different sensor and platform, is the assimilated variable. The scheme is formulated using a multi-scale approach. The misfit measure is formulated here in such a manner that LST observations with different accuracy and/or different spatial resolution, provided by different sensors, may be used together in the same assimilation sequence. A matrix of weighting factors allows to pass from each satellite resolution pixel to grid domain (Caparrini et al., 2004a). Both polar and geostationary data from different platform can be used at the same time. The benefit of using different platforms is a better estimation of LST and an increase of available data time step.

Net Radiation, wind speed, precipitation and air temperature are the forcing meteorological data. The deep ground temperature T_{deep} is estimated with a semi-diurnal filter of surface temperature (Caparrini et al., 2003).

Model provides daily EF map and hourly energy fluxes inside the daytime window.

5.1 Case Studies

The variational model has been validated over the US Southern Great Plains site, from June 18th to July 18th 1997, on a subdomain of about 64000 km², where measurements of surface fluxes from eddy correlation stations and soil moisture from ESTAR L band radiometer were available. LST from GOES, AVHRR and SSM/I sensors are assimilated over the specified region every 30 minute, when data are available. Micrometeorological data from the US Department of Energy's Atmospheric Radiation Measurement (ARM) archive, interpolated over the grid domain (4 km × 4 km) are used as forcing data. The gridded precipitation field (WSR-88D Nexrad radar calibrated precipitation estimates) created by the Hydrometeorological Analysis Support forecasters at the Arkansas Red Basin River Forecast Center, and the raingauge measurements are used as precipitation input. The application on the SGP site has shown consistent estimation of hourly turbulent fluxes and daily EF with ground measurements (Fig. 1) and pattern similarities between ESTAR soil moisture fields and EF maps. EF estimated with this new approach seems to simulate with a good accuracy the real conditions, especially when evaporation approaches its potential values. Furthermore EF can be estimated continuous in time and space, also over day where LST observation are not available. A significant improvement was obtained using precipitation radar data instead of gauge data interpolated over the domain. This experiment has prepared the path for applications on areas where heat fluxes and soil moisture measurements are not available. Model output could make up for the lack of measurements on that region and provide a better distributed data.

The new generation of Meteosat geostationary satellites permits to easily implement this approach over European-African regions, as LST estimation can be available each 15 minutes. Two case studies over Italian regions have been set; one over

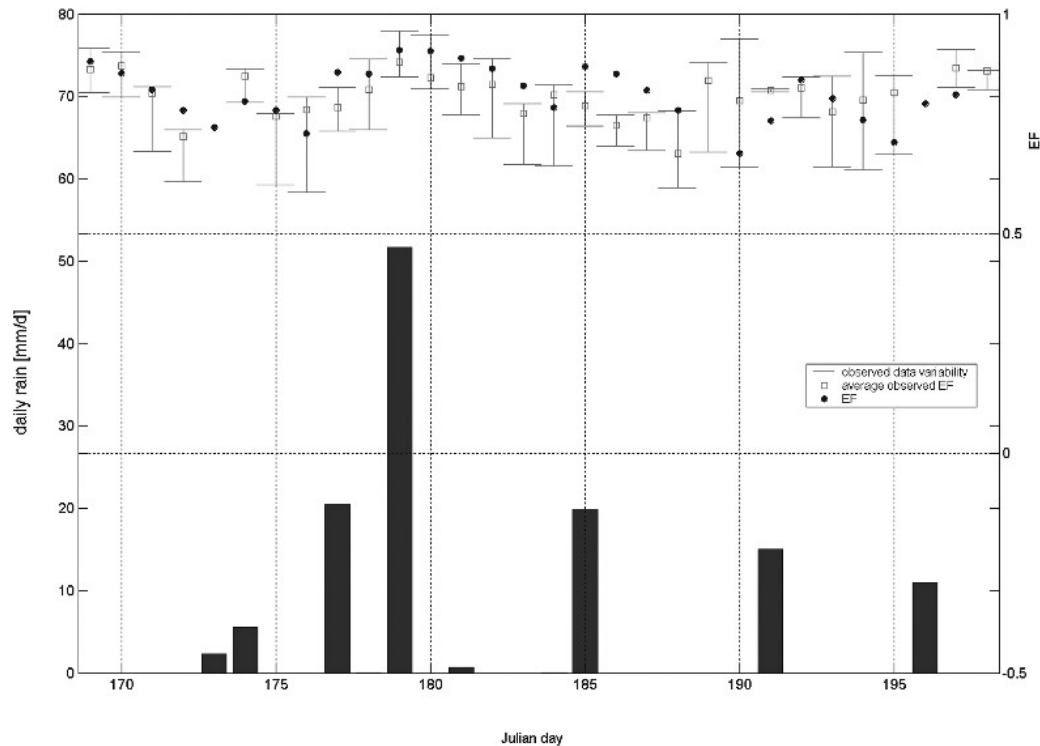


Fig. 1 SGP97 case study, El Reno site – Comparison between daily modeled and measured evaporative fraction EF. *Right axis-Black dot*: modeled EF. *Red Square*: average measured values. *Red bars* indicate the range of measurements values. Several ground stations data are available for this site. *Left axis-Blue histogram*: Daily precipitation values (See also Plate 18 in the Colour Plate Section)

Basilicata, a southern semi-arid region, and another over Tanaro, a northern-western basin. A dataset of SEVIRI, AVHRR and MODIS images and micrometeorological data from the regional micrometeorological and raingauge networks are available. The computational square grid size has been set of about 3 km, for both experiment fields. A split window algorithm (Sobrino and Romaguera, 2004; Ulivieri et al., 1992) has been applied to estimate LST from SEVIRI and AVHRR data. A threshold cloud mask, computationally fast and suitable for operational and automated detection, has been implemented and applied to each pixel of SEVIRI data (Fig. 2). MODIS and AVHRR cloud mask and MODIS LST products are provided. In both case studies model is able to simulate the LST with an accuracy inside 2–4 degrees, and the diurnal circle is captured even if few satellite images are available for that day (see Fig. 3).

The period of study over Basilicata region (about 10000 km²) covers one month, from 12th of June to 11th of July 2004. For this case study also Limited Area Model (LAM) forecast fields by Lokal Modell (Doms and Schaettler, 1999; Corazza and Sacchetti, 2005) of air temperature, net radiation and wind speed have been provided. Model performance using both meteorological forcing has been tested. Land use and vegetation cover patterns seem well captured (see Fig. 4–5). Physical values of the estimated parameters for both cases are comparable to those reported

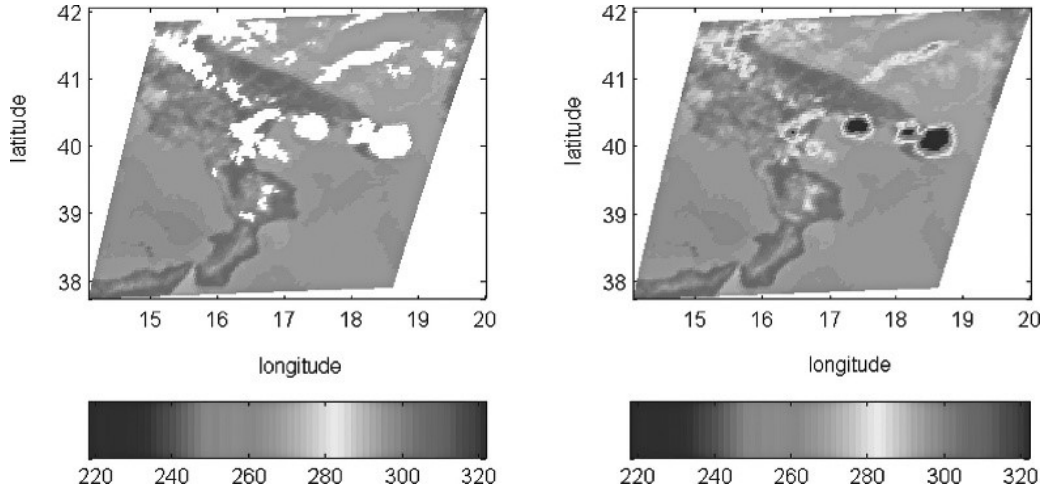


Fig. 2 Southern Italy – Example of cloud mask product. *Left*: cloud mask applied to SEVIRI “IR 10.8” data. *Right*: SEVIRI “IR 10.8” data - Brightness temperature [K] (June 26th, 2004 – 13.15 UTC) (See also Plate 19 in the Colour Plate Section)

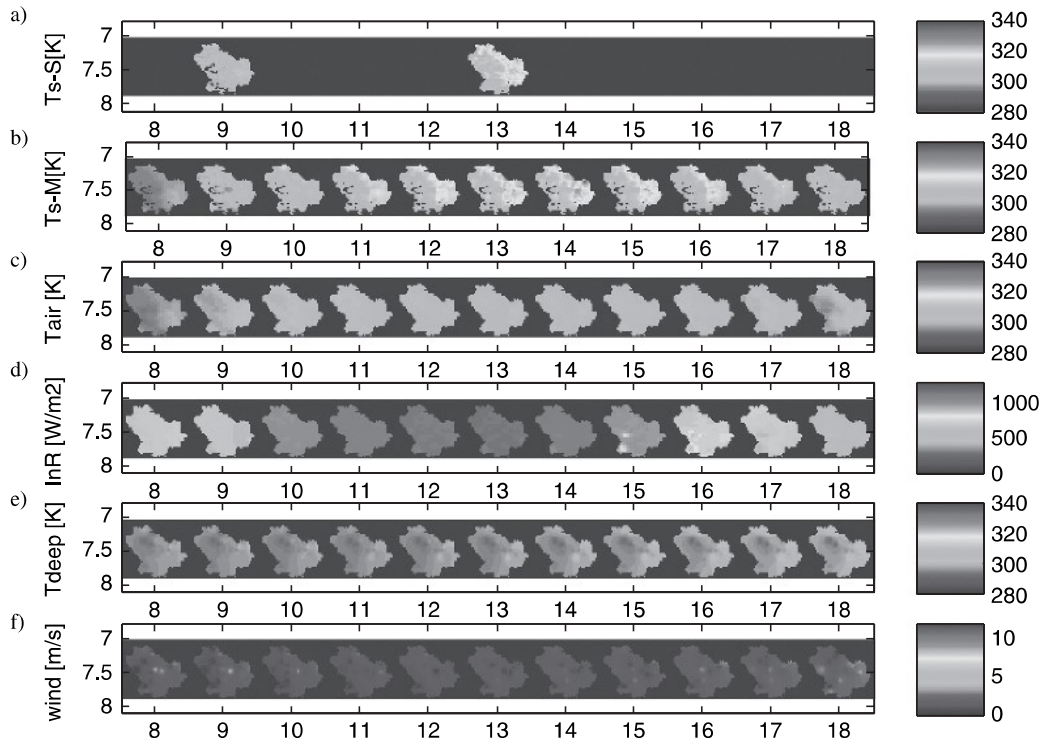


Fig. 3 Basilicata case study – Julian day 180: Daily set-up, from 8 am to 6 pm, of LST and micrometeorological forcing at 1 hour time step. (a) Observed LST [K], (b) Modeled LST [K], (c) Air temperature [K], (d) Incoming net radiation [W/m^2], (e) Ground temperature [K], (f) Wind velocity [m/s]. The calculation grid size is $3 \text{ km} \times 3 \text{ km}$. Micrometeorological data from ground station (air temperature, incoming net radiation, wind speed) are interpolated and resampled at grid resolution (See also Plate 20 in the Colour Plate Section)

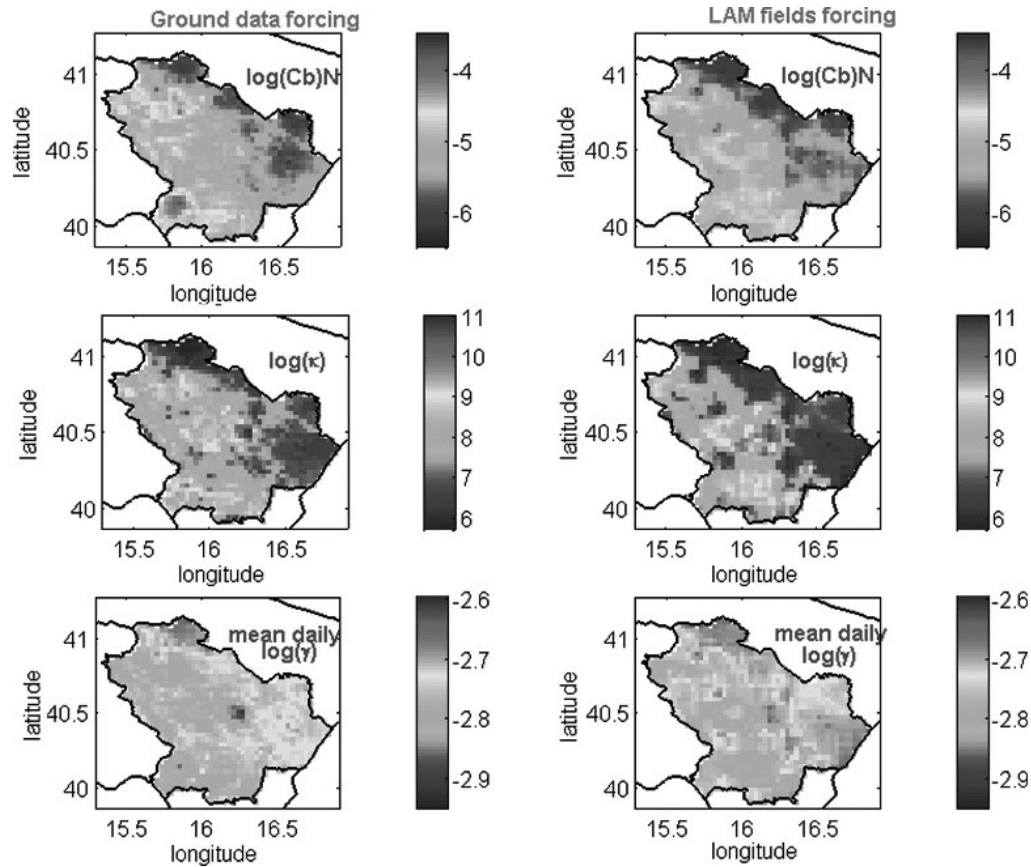


Fig. 4 Basilicata case study –Logarithmic maps of estimated parameters: neutral bulk transfer coefficient [$\log(C_B)N$], land use index K [$\log(K)$] and the averaged daily values of API decay factor [$\log(\gamma)$]. In the *left* and *right* side parameters maps, obtained using respectively interpolated ground data and LAM fields as forcing, are shown (See also Plate 21 in the Colour Plate Section)

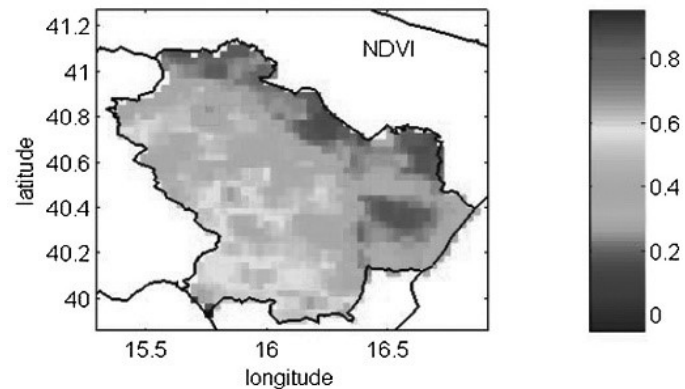


Fig. 5 Basilicata region – Normalized Difference Vegetation Index (NDVI) product by SEVIRI data, June 2004 (See also Plate 22 in the Colour Plate Section)

in literature (Stull, 1994). Checked anomalies in $\log(C_B)_N$ pattern compared with land use-NDVI map, in the case of using interpolated ground data as forcing, could be due to an adjustment of the model to measurements errors, especially to wind observations. Modelled temperatures are closer to the observations using forecast fields as forcing. It is probably due to the poor quality of ground stations dataset. Results are promising and the use of LAM fields open the possibility to implement model over ungauged area or over bigger portion of territory, difficult to manage using data from different sources and owner networks, or when data quality is not assured. Final goal of this study is to verify the possibility of using estimated evaporative fraction for improving the framework of atmosphere-surface interaction processes and calibration of hydrological models. Tanaro basin has been selected as rainfall-runoff model (Gabellani, 2005) was already implemented over that region. The variational scheme has been implemented from 27th september to 18th november 2005. Averaged estimated evaporative fraction over the Orba sub-basin (see Fig. 6) has been used to calibrated the hydrological model, as an alternative source to runoff measurements Q . Previous results (Gabellani et al., 2005) show the promise of this approach over ungauged river, but the need of a major interaction and fusion between the surface balance scheme and hydrological model. Both Q and EF could be used for improving processes schematization due to their competitive nature into model, given a good knowledge of the relevant processes.

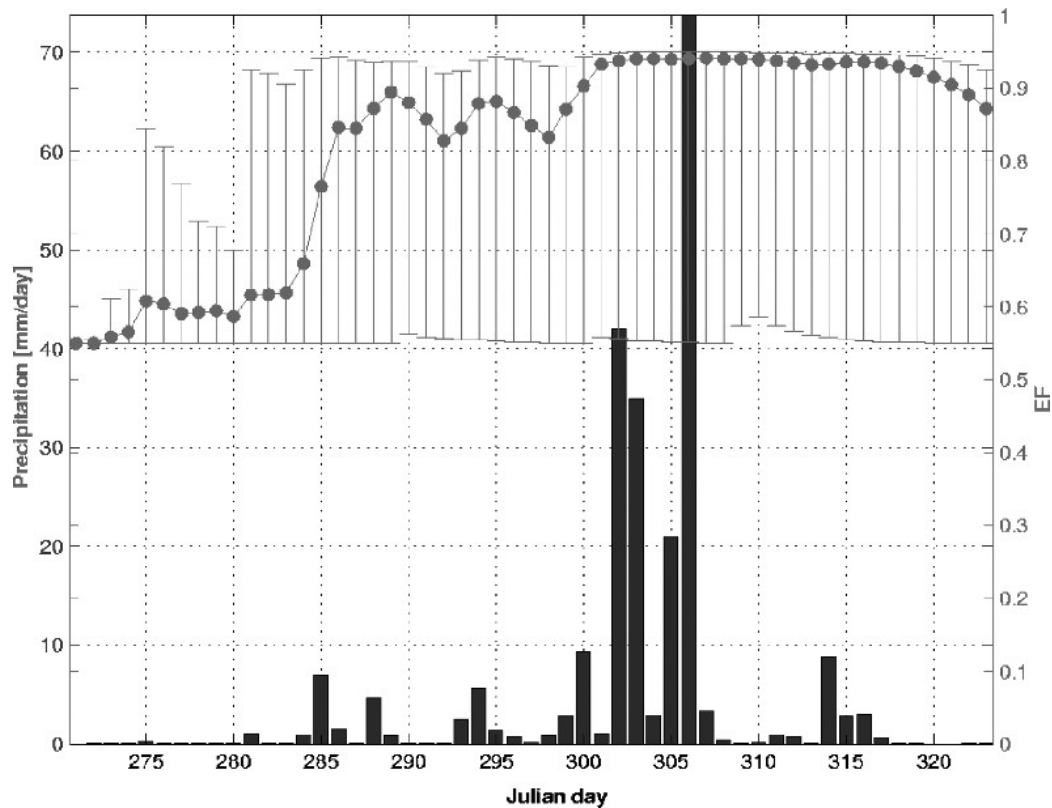


Fig. 6 Tanaro case study. *Right axis-Red dots:* estimated EF averaged over Orba basin. Bars indicate the pixels values range. *Left axis-Daily precipitation averaged over the domain* (See also Plate 23 in the Colour Plate Section)

6 Concluding Remarks and Open Questions

The estimation of the different components of the energy balance at the land surface is recognized to be a crucial research field in many hydrological and meteorological problems. Many water resources and agricultural management applications require the knowledge of surface evaporation and evaporative fraction over a range of spatial and temporal scales. Over large areas remote sensing is the only realistic either economically or logistically technique that can provide the requested coverage. Remote sensing however cannot readily provide directly heat fluxes measurements or atmospheric variables of the energy balance. Consequently, the combined use of remote sensing and ancillary surface and atmospheric observations seems to be the winner approach to solve this kind of problem. Data assimilation techniques with modeling may take advantage of both data reaching the best efficiency. LST assimilation scheme, that takes into account the surface energy balance and simplified soil moisture dynamics, represents a promise as operational tool for the monitoring of surface energy fluxes and the EF estimation, under a variety of land cover types and environmental conditions. However research must continue to investigate on the reliability of retrieved fluxes when radiation is the limiting factor, or over mostly cloudy periods, when LST observations are more affected by errors or not available. Future research should be oriented towards a major interaction and fusion between the land surface balance scheme and hydrological-meteorological models.

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